
Generation of Simulated Daily Precipitation and Air and Soil Temperatures

Paul D. Mitchell

Working Paper 00-WP 234

January 2000



Center for Agricultural and Rural Development

GENERATION OF SIMULATED DAILY PRECIPITATION AND AIR AND SOIL TEMPERATURES

Paul D. Mitchell

Working Paper 00-WP 234
January 2000

Center for Agricultural and Rural Development
Iowa State University
Ames, IA 50011-1070
www.card.iastate.edu

Paul D. Mitchell is an assistant professor, Department of Agricultural Economics, Texas A&M University.

For questions or comments about the contents of this paper, please contact Paul D. Mitchell, Texas A&M University, 333 Blocker Building, College Station, TX 77843-2124. Ph: (409)845-6322, Fax (409)862-1563, and e-mail p-mitchell@tamu.edu.

Permission is granted to reproduce this information with appropriate attribution to the author and the Center for Agricultural and Rural Development, Iowa State University, Ames, Iowa 50011-1070.

Iowa State University does not discriminate on the basis of race, color, age, religion, national origin, sexual orientation, sex, marital status, disability, or status as a U.S. Vietnam Era Veteran. Any persons having inquiries concerning this may contact the Director of Affirmative Action, 318 Beardshear Hall, 515-294-7612.

Abstract

This paper describes a maximum likelihood method using historical weather data to estimate a parametric model of daily precipitation and maximum and minimum air temperatures. Parameter estimates are reported for Brookings, SD, and Boone, IA, to illustrate the procedure. The use of this parametric model to generate stochastic time series of daily weather is then summarized. A soil temperature model is described that determines daily average, maximum, and minimum soil temperatures based on air temperatures and precipitation, following a lagged process due to soil heat storage and other factors.

Key words: Air temperatures, maximum soil temperatures, minimum soil temperatures, parametric model, precipitation, soil heat storage, stochastic time series.

Generation of Simulated Daily Precipitation and Air and Soil Temperatures

Introduction

Time series of daily weather variables such as precipitation and maximum and minimum air temperatures are used in many applications. Examples include soil temperature models (Logan et al. 1979, Gupta et al. 1981), models of arthropod or plant development (Naranjo and Sawyer 1989, Kiniry et al. 1992), and watershed hydrology models for flood control assessments (Matalas 1967). Historical data can be used for deterministic versions of these models, but if the analysis requires longer time series, generated times series that accurately reflect actual weather are needed. To assess uncertainty created by weather events, sampling with or without replacement from historical data has been used for bio-economic analysis (Pannell 1990, Mjelde et al. 1988). Because this method is limited to observed weather, however, it may not capture the full range of weather variability or shifts that have occurred due to climate change. The approach presented here estimates a parametric model of the underlying stochastic processes, then describes the generation of simulated time series that exhibit the same uncertainty as the observed daily weather. The weather model is adapted from Richardson (1981), whose model serves as the basis for WGEN, the weather generation model used by EPIC³the Erosion-Productivity Impact Calculator (Richardson and Wright 1984, Williams 1995). The soil temperature model is a modification of Potter and Williams (1994) which is also used by EPIC.

The paper begins with a brief description of the historical daily weather data used to estimate model parameters for Boone, IA, and Brookings, SD. Then the estimation process for the precipitation parametric model is described and parameter estimates are reported; the procedure is repeated for the model of air temperatures. Next, an algorithm to generate simulated time series of the weather variables using the parametric model is summarized. Lastly, a model that determines soil temperatures as functions of air temperatures and precipitation is described.

Historical Weather Data

The National Climatic Data Center's (NCDC) Validated Historical Daily Data was obtained on CD-ROM for hundreds of weather stations throughout the United States (EarthInfo 1996). Using the accompanying software package, all observations of the daily maximum and minimum air temperature and total precipitation for weather stations in Brookings, SD, and Boone, IA, were exported. For Brookings this information included observations from January 1, 1893, to December 31, 1994, (102 years or 37,230 days), with 441 days missing (<1.2 percent). For Boone the observations covered May 1, 1948, to December 31, 1994, (47 years or 16,837 days), with 228 days missing (< 1.35 percent). These data were used to estimate all parameters for stochastic temperature and precipitation generation. In leap years, data for February 29 were deleted so that every year had 365 days. The error introduced by this deletion occurred during a period generally unimportant to crop production in the Midwest. The econometrics software package Time Series Program (TSP) 4.3 (TSP International 1995) was used to estimate all parameters. The TSP defaults for missing data points were used.

Precipitation Model Parameter Estimation

Markov Model of Daily Precipitation Status

Following Richardson (1981), assume a first-order Markov chain model with two states that generates the observed series of wet and dry days. A first-order Markov chain is defined by its transition matrix, which contains the probabilities that the process transitions from one state to the next, conditional on the current state. Typically, rows represent current states and columns represent future states for a transition matrix (Lial et al. 1998). A transition matrix must be square, because all possible states of the process must be used as both rows and columns. Furthermore, each row sums to one because the process must end in one of the states specified by the process.

For the process modeled here there are two states: a day is either wet or dry. The probability that a day is wet or dry is conditional on whether the previous day was wet or dry. This is summarized in the transition matrix P : $P = \begin{bmatrix} P_{dd} & P_{dw} \\ P_{wd} & P_{ww} \end{bmatrix} = \begin{bmatrix} P_{dd} & 1 - P_{dd} \\ P_{wd} & 1 - P_{wd} \end{bmatrix}$, where P_{dd} is the probability of a dry day following a dry day and P_{wd} is the probability of a dry day following a

wet day, using the convention that row subscripts define current states and column subscripts define future states. Thus, the precipitation status for any given day is completely defined by the two parameters P_{dd} and P_{wd} ; however, a total of 730 parameters must be estimated, because parameter values are specific to each day and there are 365 days in a year.

To reduce the number of parameters, the seasonal periodicity exhibited by the transition probabilities is utilized. Following the maximum likelihood method described by Woolhiser and Pegram (1979), a Fourier series is estimated for each transition probability. First the number of observed transitions from each state on each day of the year is calculated and denoted a_{ij}^n , where $i\hat{I}\{d,w\}$ and indexes current states, $j\hat{I}\{d,w\}$ and indexes future states, and n denotes the day of the year. The log-likelihood function is:

$$\ln L(\phi | X) = \sum_{n=1}^{365} \left[a_{dd}^n \ln(P_{dd}(n)) + a_{dw}^n \ln(1 - P_{dd}(n)) + a_{wd}^n \ln(P_{wd}(n)) + a_{ww}^n \ln(1 - P_{wd}(n)) \right], \quad (1)$$

$$P_{dd}(n) = A_d + \sum_{k=1}^{H_d} \left[C_{dk} \cos\left(\frac{nk}{K}\right) + S_{dk} \sin\left(\frac{nk}{K}\right) \right], \quad (2)$$

$$P_{wd}(n) = A_w + \sum_{k=1}^{H_w} \left[C_{wk} \cos\left(\frac{nk}{K}\right) + S_{wk} \sin\left(\frac{nk}{K}\right) \right], \quad (3)$$

where $K = 365/2p \gg 58.091554$ is the necessary normalizing constant; H_d and H_w are the number of harmonics estimated for P_{dd} and P_{wd} , respectively; f is the parameter vector of Fourier coefficients $\{A_d, A_w, C_{dk_d}, S_{dk_d}, C_{wk_w}, S_{wk_w}\}$; and X is the matrix of the a_{ij}^n , the number of observed transitions. The number of harmonics for each Fourier series is increased one at a time until the addition of a harmonic fails a Likelihood Ratio test at the 5 percent level of significance. The maximum likelihood estimates and standard errors are reported in Table 1 for Brookings and Boone; Figures 1 and 2 illustrate the fit and smoothing of the data provided by the Fourier series.

Exponential Model of Daily Precipitation

Several alternatives are available for a stochastic model of the amount of precipitation on wet days, but Richardson's exponential model was chosen for its simplicity. Define R_n as the amount of precipitation on a given day n when n is a wet day. Assume R_n is distributed according to the exponential distribution with probability density function $f(R_n) = \lambda_n e^{-\lambda_n R_n}$, where λ_n is

specific to each day. As with the transition probabilities, the seasonal periodicity exhibited by the l_n is used to reduce the number of required parameters.

Following the maximum likelihood method described by Woolhiser and Pegram (1979), a Fourier series is estimated for the parameter l . To express the log-likelihood function, define R_{ny} as the observed amount of precipitation for day n in year y , and define

$D_{ny} = \begin{cases} 0 & \text{if } R_{ny} = 0 \\ 1 & \text{if } R_{ny} > 0 \end{cases}$. Then the log-likelihood function is:

$$\ln L(\theta | R, D) = \sum_{n=1}^{365} \sum_{y=1}^T D_{ny} [\ln(\lambda(n)) - \lambda(n)R_{ny}], \quad (4)$$

$$\lambda(n) = A + \sum_{k=1}^H \left[C_k \cos\left(\frac{nk}{K}\right) + S_k \sin\left(\frac{nk}{K}\right) \right], \quad (5)$$

where q is the parameter vector of Fourier coefficients $\{A, C_k, S_k\}$, T is the number of years, and H is the number of harmonics. For estimation, the number of harmonics is increased one at a time until the addition of a harmonic fails a Likelihood Ratio test at the 5 percent level of significance. The maximum likelihood estimates and standard errors are reported in Table 2 for Brookings and Boone; Figure 3 illustrates the fit and smoothing of the data provided by the Fourier series.

Air Temperature Model Parameter Estimation

Daily Mean and Standard Deviation of Maximum and Minimum Air Temperatures

Following the procedure described by Richardson (1981) and Matalas (1967), assume that daily maximum and minimum air temperatures are a continuous, multivariate, weakly stationary process with daily means and standard deviations conditional on the wet or dry state of the day. For each day of the year, calculate the mean and standard deviation of the maximum and minimum air temperatures separately for wet and dry days. This calculation yields eight parameter estimates for each day of the year: the wet and dry mean and the wet and dry standard deviation for the maximum temperature, and the same four for the minimum temperature. Again utilize seasonal periodicity to reduce this set of parameters by using a least squares criterion to estimate eight separate Fourier series. The general equation used for each series is:

$$\theta(n) = A + \sum_{k=1}^H \left[C_k \cos\left(\frac{nk}{K}\right) + S_k \sin\left(\frac{nk}{K}\right) \right], \quad (6)$$

where q is the parameter for which the Fourier series is being estimated and n is the day of the year. The estimated coefficients are A , the C_k and S_k , and H , the number of harmonics for the series. For each Fourier series, harmonics are increased one at a time until the addition of a harmonic fails a Likelihood Ratio test at the 5 percent level of significance. Coefficient estimates and standard errors for all eight Fourier series for both Brookings and Boone are reported in Tables 3–10; Figures 4–11 illustrate the fit provided by the Fourier series for both locations.

Maximum and Minimum Air Temperature Residuals

Following the method described by Matalas (1967), calculate the maximum and minimum temperature residuals for each observation by subtracting the appropriate wet or dry mean observed on that day of the year (not estimated by the Fourier series) and dividing by the appropriate wet or dry standard deviation observed on that day of the year. The temperature residuals for any day of the year are the deviation of observed temperatures from the appropriate wet or dry mean, normalized by the appropriate wet or dry standard deviation. Next assume that the maximum and minimum air temperature residuals follow a multivariate weakly stationary process defined by:

$$\chi_{n+1,y} = A\chi_{n,y} + B\epsilon_{n+1,y} \quad (7)$$

where $e_{n,y}$ is a (2 x 1) matrix of independently distributed standard normal (mean zero, variance one) random variables for the specified day and year, and $c_{n,y}$ and $c_{n+1,y}$ are (2 x 1) matrices of the maximum and minimum air temperature residuals for the specified day and year.

A and B are (2 x 2) matrices whose elements are functions of the lag 0 and lag 1 serial- and cross-correlation coefficients of the observed residuals, defined so that any series of residuals generated by a series of standard normal errors exhibits the same serial- and cross-correlation as the observed residuals. Note (7) implies that the residuals are normally distributed and follow a first-order linear autoregressive process. A and B are determined by the following equations:

$$A = M_1 M_0^{-1} \quad (8)$$

$$BB^T = M_0 - M_1 M_0^{-1} M_1^T. \quad (9)$$

M_0 and M_1 are matrices of the lag 0 and lag 1 correlation coefficients, respectively, defined as follows:

$$M_0 = \begin{bmatrix} 1 & \rho_{X_0 N_0} \\ \rho_{N_0 X_0} & 1 \end{bmatrix} \quad (10)$$

$$M_1 = \begin{bmatrix} \rho_{X_0 X_{-1}} & \rho_{X_0 N_{-1}} \\ \rho_{N_0 X_{-1}} & \rho_{N_0 N_{-1}} \end{bmatrix}, \quad (11)$$

where X and N denote the residuals for the maximum and minimum air temperature, respectively, and their subscripts denote lag 0 or lag 1. Thus $\rho_{X_0 N_0}$ is the lag 0 cross-correlation coefficient between the residuals for the maximum air temperature and the residuals for the minimum air temperature. $\rho_{X_0 X_{-1}}$ and $\rho_{N_0 N_{-1}}$ are the lag 1 serial correlation for the residuals of the maximum and minimum air temperature, respectively. $\rho_{X_0 N_{-1}}$ is the cross-correlation coefficient between the lag 0 maximum air temperature residuals and the lag 1 minimum air temperature residuals, and $\rho_{N_0 X_{-1}}$ is the cross-correlation coefficient between the lag 0 minimum air temperature residuals and the lag 1 maximum air temperature residuals. Table 11 reports the serial-correlation and cross-correlation coefficients needed to construct the M_0 and M_1 matrices for Brookings and Boone.

To solve (9) for B , first define a matrix $Z = BB^T$. Using spectral decomposition, $Z = CLC^T$, where C is the matrix of eigenvectors, and L is the matrix with the associated eigenvalues down the main diagonal and zeros for all other elements [see Greene (1997), p. 38]. Note that $BB^T = Z^{1/2}Z^{1/2T} = Z$, implying that $B = Z^{1/2}$, then by Greene's Theorem 2.10, $B = Z^{1/2} = CL^{1/2}C^T$. Table 11 also reports the elements of A and B for both locations.

Generation of Simulated Weather

Extensive time series for precipitation and maximum and minimum air temperatures that exhibit appropriate serial- and cross-correlations can be generated once the parametric model is estimated. Initialize the process by specifying the previous day's maximum and minimum temperature residuals and its precipitation status as either wet or dry. Assuming that the previous day was dry and that both temperature residuals were zero seems reasonable, since a dry day is most likely for the two locations reported here and residuals of zero imply that maximum and minimum temperatures were exactly at their respective means. Also, substitute all estimated parameter values into the appropriate Fourier series.

In general, the algorithm proceeds by first determining the precipitation status of the current day conditional on the previous day's precipitation status, then determining the daily maximum and minimum temperatures conditional on the current day's precipitation status and the previous day's temperatures. The specifics of the algorithm are outlined in a series of steps for a given day n :

1. Calculate the probability that day n is dry by using Equation (2) if day $n - 1$ was dry or Equation (3) if day $n - 1$ was wet.
2. Draw a uniform random variable between zero and one; if it exceeds the probability that day n is dry, then day n is wet, else day n is dry.
3. If day n is dry, go to the next step, else use Equation (5) to calculate l and draw the precipitation amount as an exponential random variable with mean $1/l$.
4. Draw two independent standard normal random variables to construct the e matrix, then use Equation (7) to calculate the maximum and minimum air temperature residuals.
5. Calculate the mean and standard deviation of the maximum and minimum air temperatures using the appropriate forms of Equation (6) depending on the precipitation status of day n .
6. Calculate day n 's maximum and minimum air temperature by multiplying each residual by the appropriate standard deviation and adding the appropriate mean.

The generation of reliable random numbers using computers is an essential part of generating simulated weather data but is not a simple process. Press et al. (1992) expressly warn researchers against using random numbers supplied by software systems, because the series of numbers may quickly repeat itself. Repetition of random series is a real concern if rather long time series are needed, as can be the case for Monte Carlo analysis. Press et al. (1992) describe several algorithms for generating uniform random variables (e.g., L'Ecuyer's long-period generator with a Bays-Durham shuffle) and transformation techniques for obtaining random variables from other distributions from uniform random variables.

Soil Temperature Model

Soil temperatures in the top soil layer are important in crop production. Soil temperatures determine the germination and growth of planted crops and weeds, as well as regulate the meta-

bolic activity and development of soil microbes, nematodes, fungi, worms, and insects. This section presents a model of soil temperatures in the top 10-cm layer. The method of Potter and Williams (1994) is used with a few modifications to determine the daily average soil temperature as a function of air temperature. The method of Logan et al. (1979) is modified in accordance with data presented in Gupta et al. (1983) to determine the daily maximum and minimum soil temperatures as functions of the average soil temperature.

Average Soil Temperature

The model of Potter and Williams (1994) derives the average soil temperature for a layer below the surface by first modeling the temperature of the bare soil surface, which closely follows the air temperatures, then adjusting this bare soil surface temperature to account for soil cover. Next, a physically derived depth-weighting factor (DWF) is used to determine the average soil temperature at any given depth between the soil surface and the constant temperature depth. Following their model, $PTBS_n$, the potential temperature of the bare soil for day n , depends on a day's precipitation status as follows:

$$PTBS_n = \begin{cases} T_{Min,n} + \frac{NWD_n}{30} \alpha_n^{air} & \text{if the day is wet} \\ T_{Avg,n} + \frac{NWD_n}{30} \alpha_n^{air} & \text{if the day is dry,} \end{cases} \quad (12)$$

where NWD is the number of wet days over the past thirty days (including the current day);

$T_{Max,n}$, $T_{Min,n}$, and $T_{Avg,n}$ are the maximum, minimum, and average air temperatures for day n (the average temperature is the simple average of the maximum and minimum); and

$\alpha_n^{air} = \frac{1}{2}(T_{Max,n}^{air} - T_{Min,n}^{air})$ is the amplitude of the temperature change on day n . The actual temperature of the bare soil (TBS_n) is then the two-day moving average of the $PTBS$.

Next, the average soil surface temperature for day n ($T_{Avg,n}^{surface}$) uses the TBS , but accounts for soil cover by using a lagged cover factor (LCF_n) as follows:

$$T_{Avg,n}^{surface} = LCF_n TBS_{n-1} + (1 - LCF_n) TBS_n \quad (13)$$

$$LCF_n = MAX\{BCF_n, SCF_n\}. \quad (14)$$

BCF_n is the biomass cover factor and SCF_n is the snow cover factor for day n calculated by the following empirically derived equations:

$$BCF_n = \frac{B_n}{B_n + \exp(5.3396 - 2.3951B_n)} \quad (15)$$

$$SCF_n = \frac{S_n}{S_n + \exp(2.303 - 0.2197S_n)}, \quad (16)$$

where B_n is the total above ground crop biomass and surface residue (Mg/ha) and S_n is the water content of the snow cover (mm) on day n . After validating the model with data from three locations, Potter and Williams impose the following restrictions:

$0 \leq BCF_n \leq 0.19$ and $0 \leq SCF_n \leq 0.95$.

To determine B_n , the base cover contributed by crop residue is assumed to be 1.4 Mg/ha, which is approximately the amount of residue left from continuous corn production under conventional tillage. This is calculated by assuming a 1:1 ratio of grain to residue production for corn, following Larson et al. (1978, cited in Havlin et al. 1990) and assuming a bushel of corn weighs 56 lbs. (USDA 1979). Thus a typical yield for Brookings of 100 bu/ac implies 6.3 Mg/ha of residue and a typical yield for Boone of 150 bu/ac implies 9.4 Mg/ha. Standard tillage operations for conventional tillage corn are from state extension budgets for South Dakota (chisel plow and tandem disk) and Iowa (chisel plow, tandem disk, and field cultivator) (SDSU Extension Economics 1998, ISU Extension 1998). Residue mixing efficiencies typical for these operations are from the EPIC User's Guide: chisel plow, 0.42; tandem disk, 0.50; field cultivator, 0.70 (Mitchell et al. 1997). Then, $6.3 \times 0.42 \times 0.50 = 1.32$ and $9.4 \times 0.42 \times 0.50 \times 0.70 = 1.38$ are rounded up to 1.4 to serve as a simple estimate of the base cover from crop residue.

To include the contribution of growing crop biomass to B_n , the year is divided into four periods roughly coinciding with seasons: (1) no living crop biomass, (2) linear biomass accumulation during crop growth, (3) maintenance of living crop biomass during summer, and (4) linear decline of crop biomass during senescence and harvest. For each of these periods, the value of B_n is determined as follows:

November 1 to plant day	$B_n = 1.4$	(17a)
-------------------------	-------------	-------

$$\text{Plant day to peak flower} \quad B_n = 1.4 + 7 \left(\frac{\text{current day} - \text{plant day}}{\text{peak flower} - \text{plant day}} \right) \quad (17b)$$

$$\text{Peak flower to harvest} \quad B_n = 9.4 \quad (17c)$$

$$\text{Harvest to November 1} \quad B_n = 9.4 - 7 \left(\frac{\text{current day} - \text{harvest}}{305 - \text{harvest}} \right). \quad (17d)$$

Plant days range from early May to early June, with early to mid-May typical. Peak flower depends on the maturity of the corn hybrid and occurs from early August to mid-September, with mid- to late August typical. Harvest can range from as early as late September to as late as late November, but mid-October is typical.

To determine S_n , the water content of snow cover (mm), a model of snowfall accumulation and snowmelt is used. If precipitation occurs on a day, it is categorized as snowfall if the maximum air temperature is less than 40° F and the average is below 35° F. The multiple-layer soil temperature model of snowmelt developed by Williams (1995) is adapted to the single-layer soil temperature model used here. If a snow pack is present and the average soil temperature on day n ($T_{Avg,n}^{soil}$) is above zero, then the millimeters of snowmelt on day n (SM_n) occurs according to the empirically derived equation:

$$SM_n = T_{Avg,n} (1.52 + 0.54 \text{MIN} \{T_{Avg,n}^{soil}, T_{Avg,n}\}). \quad (18)$$

The method of Potter and Williams (1994) is then used to determine the daily average soil temperature at 5 cm, the middle of the top 10 cm of soil, as follows:

$$T_{Avg,n}^{soil} = 0.5T_{Avg,n-1}^{soil} + 0.5T_{Avg,n}^{surface} + 0.5DWF(\bar{T} - T_{Avg,n}^{surface}). \quad (19)$$

\bar{T} is the long-term average air temperature that approximates the constant soil temperature maintained at some sufficient depth (6.2°C for Brookings and 8.5°C for Boone) and DWF is the depth-weighting factor. Potter and Williams's Equations (7) – (11) were used to determine the value of DWF over a wide range of soil bulk density and soil water conditions. The value changes very little (0.2237 - 0.2260), even under extraordinarily unlikely conditions, so an average value of 0.225 is used for all simulations. Because Potter and Williams note that the model tends to underpredict average soil temperatures, the average is increased by 2.5 percent.

Maximum and Minimum Soil Temperatures

To determine the daily maximum and minimum soil temperatures, the method of Logan et al. (1979) is modified to extrapolate from air temperature extremes to near-surface soil temperature extremes. Their method was developed to extrapolate from measured temperatures at one depth to temperatures at another depth, not from surface to below-ground temperatures. Essentially, the method assumes that the amplitude at one depth is proportional to the amplitude at another depth, with the constant of proportionality depending on the difference in depth. Using Logan et al.'s Equation (9) gives a value of 0.98 for a depth difference of 10 cm. Assuming that the soil surface temperature is the same as the air temperature, this factor implies that the amplitude of soil temperatures at 5 cm is 98 percent of the amplitude of the air temperature. However, this does not account for dampening due to soil cover, nor due to additional heat input from solar radiation, especially significant in spring when the soil is dark and crops do not shade the soil surface.

To adjust for soil cover, the constant of proportionality is reduced to 0.95 for days between March 1 and November 15 (approximately soil thaw to soil freeze). Benoit and Van Sickle (1991) report data on winter soil temperatures for various tillage-residue management systems in west central Minnesota. These data indicate that the difference between the maximum and minimum air temperatures is around 10–12°C, whereas the difference between the maximum and minimum soil temperatures at 5 cm is about 2–4°C, or about 25 percent less. Thus from November 15 to March 1, the constant of proportionality is set to 0.25.

Research has also shown that the variation of near-surface soil temperatures around the average is asymmetric and changes throughout the season due to tillage and crop growth (Gupta et al. 1981, Gupta et al. 1983, Potter and Williams 1994). Data reported by Gupta et al. (1983) indicate that in spring the maximum soil temperature is approximately 25 percent more above the average soil temperature than the maximum air temperature is above the average air temperature. This occurs because the soil is generally dark and no crops provide shade. In summer, the factor is approximately 15 percent because solar radiation has increased, but crops begin to provide increasingly more shade.

All these adjustments are summarized in the equations used to determine the soil maximum and minimum temperatures:

Spring (March 1 to plant day + 42 days):

$$T_{Max,n}^{soil} = 1.25[T_{Avg,n}^{soil} + 0.95\alpha_n^{air}] \quad (20a)$$

$$T_{Min,n}^{soil} = 1.00[T_{Avg,n}^{soil} - 0.95\alpha_n^{air}] \quad (20b)$$

Summer (plant day + 42 days to September 15):

$$T_{Max,n}^{soil} = 1.15[T_{Avg,n}^{soil} + 0.95\alpha_n^{air}] \quad (21a)$$

$$T_{Min,n}^{soil} = 1.00[T_{Avg,n}^{soil} - 0.95\alpha_n^{air}] \quad (21b)$$

Fall (September 15 to November 15):

$$T_{Max,n}^{soil} = 1.00[T_{Avg,n}^{soil} + 0.95\alpha_n^{air}] \quad (22a)$$

$$T_{Min,n}^{soil} = 1.00[T_{Avg,n}^{soil} - 0.95\alpha_n^{air}] \quad (22b)$$

Winter (November 15 to March 1):

$$T_{Max,n}^{soil} = 1.00[T_{Avg,n}^{soil} + 0.25\alpha_n^{air}] \quad (23a)$$

$$T_{Min,n}^{soil} = 1.00[T_{Avg,n}^{soil} - 0.25\alpha_n^{air}] \quad (23b)$$

The overall performance of the soil temperature model is difficult to evaluate without comparing to actual data. However, the model is based on assumptions and equations well-tested in the literature; e.g., Potter and Williams (1994) is the soil temperature model used for EPIC. The soil temperature model developed here predicts the daily average, maximum, and minimum soil temperature as a function of the daily maximum and minimum air temperature and precipitation status (wet or dry). Furthermore, the model accounts for the impact of crop growth and seasonal changes, including snowfall accumulation.

Conclusion

This paper describes the estimation of a parametric model of daily precipitation and maximum and minimum air temperatures and the use of that model to generate simulated time series of weather variables. Maximum likelihood equations for estimating the parametric model using historical data are provided and parameter estimates for Brookings, SD, and Boone, IA, are reported. Alternative specifications of the parametric model could be explored to improve the modeling of the underlying stochastic processes. For example, for the precipitation model, higher-order Markov chains or multiple rainfall states could be explored, as well as more flexible distributions such as the gamma or beta for the amount of rainfall on wet days (Richardson 1981). For the daily temperature model, corrections for skewness and kurtosis could be incorporated, or nonnormal error specifications could be used (Matalas 1967). The soil temperature model could be validated by comparing model predictions with actual soil temperature data in a manner similar to that of Potter and Williams (1994).

Table 1. Fourier series coefficient estimates for the probability of a dry day following a dry day and the probability of a wet day following a dry day in Brookings, SD, and Boone, IA

Coefficient ^a	Brookings, SD		Boone, IA	
	Estimate	Standard Error ^b	Estimate	Standard Error ^b
A_d	0.7807	0.0025	0.7715	0.0037
C_{d1}	0.1031	0.0035	0.0635	0.0051
S_{d1}	-0.0094	0.0035	-0.0206	0.0053
C_{d2}	-0.0015	0.0034		
S_{d2}	0.0183	0.0036		
C_{d3}	-0.0063	0.0034		
S_{d3}	-0.0128	0.0035		
A_w	0.7712	0.0048	0.5716	0.0076
C_{w1}	0.0967	0.0071	0.0492	0.0107
S_{w1}	-0.0063	0.0064	-0.0033	0.0108
C_{w2}	-0.0034	0.0070	0.0384	0.0104
S_{w2}	0.0153	0.0065	0.0499	0.0110
C_{w3}	-0.0067	0.0068	0.0022	0.0107
S_{w3}	-0.0236	0.0067	-0.0248	0.0106

^a See Equations (2) and (3) for coefficient definitions.

^b Computed according to the method of Berndt et al. (1974).

Table 2. Fourier series coefficient estimates for the parameter l of the exponential probability density function for Brookings, SD, and Boone, IA

Coefficient ^a	Brookings, SD		Boone, IA	
	Estimate	Standard Error ^b	Estimate	Standard Error ^b
A	5.2815	0.0560	3.6183	0.0489
C_1	3.4095	0.0920	1.7404	0.0757
S_1	0.9470	0.0608	0.4353	0.0617
C_2	1.2737	0.0806	0.4926	0.0706
S_2	0.7630	0.0715	0.3211	0.0668
C_3	0.4884	0.0702	0.2207	0.0655
S_3	0.3548	0.0728	0.2046	0.0675
C_4	0.1094	0.0555	0.0404	0.0523
S_4	0.3386	0.0580	0.2009	0.0565

^a See Equation (5) for coefficient definitions.^b Computed according to the method of Berndt et al. (1974).

Table 3. Fourier series coefficient estimates for the mean of the maximum air temperature on a dry day for Brookings, SD, and Boone, IA

Coefficient ^a	Brookings, SD		Boone, IA	
	Estimate	Standard Error ^b	Estimate	Standard Error ^b
A	56.2517	0.0617	60.4045	0.0939
C_1	-29.5203	0.0872	-28.0091	0.1328
S_1	-9.4464	0.0872	-8.5034	0.1328
C_2	-3.0251	0.0872	-3.0917	0.1328
S_2	-0.6941	0.0872	-1.0609	0.1328
C_3	0.1797	0.0872	-0.2957	0.1328
S_3	-0.2027	0.0872	0.3601	0.1328
C_4	0.3126	0.0872	-0.1516	0.1328
S_4	0.8663	0.0872	0.7117	0.1328

^a See Equation (6) for coefficient definitions.^b Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 4. Fourier series coefficient estimates for the mean of the maximum air temperature on a wet day for Brookings, SD, and Boone, IA

Coefficient ^a	Brookings, SD		Boone, IA	
	Estimate	Standard Error ^b	Estimate	Standard Error ^b
A	51.9957	0.1353	57.3062	0.1533
C_1	-30.5627	0.1914	-27.7780	0.2168
S_1	-9.3814	0.1914	-9.0578	0.2168
C_2	-2.2156	0.1914	-2.3425	0.2168
S_2	-0.3683	0.1914	-1.0260	0.2168
C_3	-0.0083	0.1914		
S_3	-0.6594	0.1914		

^a See Equation (6) for coefficient definitions.

^b Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 5. Fourier series coefficient estimates for the mean of the minimum air temperature on a dry day for Brookings, SD, and Boone, IA

Coefficient ^a	Brookings, SD		Boone, IA	
	Estimate	Standard Error ^b	Estimate	Standard Error ^b
A	31.2684	0.0552	35.7891	0.0851
C_1	-26.3254	0.0781	-25.4551	0.1204
S_1	-8.3304	0.0781	-7.6758	0.1204
C_2	-1.4249	0.0781	-1.2151	0.1204
S_2	-0.5198	0.0781	-0.6731	0.1204
C_3	-0.5433	0.0781	-0.5060	0.1204
S_3	-1.2559	0.0781	-1.0473	0.1204
C_4	0.1131	0.0781		
S_4	-0.2720	0.0781		
C_5	0.0743	0.0781		
S_5	0.3328	0.0781		
C_6	0.4958	0.0781		
S_6	-0.0171	0.0781		

^a See Equation (6) for coefficient definitions.

^b Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 6. Fourier series coefficient estimates for the mean of the minimum air temperature on a wet day for Brookings, SD, and Boone, IA

Coefficient ^a	Brookings, SD		Boone, IA	
	Estimate	Standard Error ^b	Estimate	Standard Error ^b
A	33.5774	0.1367	38.3504	0.1548
C_1	-27.1519	0.1934	-25.0132	0.2189
S_1	-8.7806	0.1934	-8.0771	0.2189
C_2	-3.0643	0.1934	-2.3501	0.2189
S_2	-1.2747	0.1934	-1.2593	0.2189
C_3	-0.7844	0.1934	-0.9538	0.2189
S_3	-1.2311	0.1934	-0.9808	0.2189

^a See Equation (6) for coefficient definitions.

^b Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 7. Fourier series coefficient estimates for the standard deviation of the maximum air temperature on a dry day for Brookings, SD, and Boone, IA

Coefficient ^a	Brookings, SD		Boone, IA	
	Estimate	Standard Error ^b	Estimate	Standard Error ^b
A	11.1102	0.0395	10.0688	0.0670
C_1	2.8808	0.0559	2.9809	0.0947
S_1	1.2214	0.0559	1.3168	0.0947
C_2	-0.5267	0.0559	-0.6754	0.0947
S_2	-0.2341	0.0559	-0.1711	0.0947
C_3	0.1342	0.0559		
S_3	0.2585	0.0559		
C_4	0.2079	0.0559		
S_4	0.3425	0.0559		
C_5	-0.1920	0.0559		
S_5	0.2608	0.0559		
C_6	-0.2079	0.0559		
S_6	0.0854	0.0559		
C_7	-0.0636	0.0559		
S_7	-0.2245	0.0559		
C_8	-0.0874	0.0559		
S_8	-0.2487	0.0559		

^a See Equation (6) for coefficient definitions.

^b Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 8. Fourier series coefficient estimates for the standard deviation of the maximum air temperature on a wet day for Brookings, SD, and Boone, IA

Coefficient ^a	Brookings, SD		Boone, IA	
	Estimate	Standard Error ^b	Estimate	Standard Error ^b
A	10.2603	0.0944	9.8459	0.1166
C_1	1.8704	0.1335	2.0811	0.1649
S_1	0.8781	0.1335	1.2429	0.1649
C_2	-0.6026	0.1335	-0.9649	0.1649
S_2	-0.5283	0.1335	-0.6009	0.1649
C_3	0.5335	0.1335		
S_3	0.4154	0.1335		

^a See Equation (6) for coefficient definitions.

^b Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 9. Fourier series coefficient estimates for the standard deviation of the minimum air temperature on a dry day for Brookings, SD, and Boone, IA

Coefficient ^a	Brookings, SD		Boone, IA	
	Estimate	Standard Error ^b	Estimate	Standard Error ^b
A	10.4959	0.0400	9.5900	0.0616
C_1	3.0695	0.0566	2.8803	0.0872
S_1	0.9792	0.0566	0.8108	0.0872
C_2	0.7013	0.0566	0.5321	0.0872
S_2	1.0220	0.0566	0.4681	0.0872
C_3	0.2662	0.0566	0.3502	0.0872
S_3	0.8091	0.0566	0.7953	0.0872
C_4	-0.1969	0.0566		
S_4	-0.2837	0.0566		
C_5	-0.1496	0.0566		
S_5	-0.3494	0.0566		

^a See Equation (6) for coefficient definitions.

^b Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 10. Fourier series coefficient estimates for the standard deviation of the minimum air temperature on a wet day for Brookings, SD, and Boone, IA

Coefficient ^a	Brookings, SD		Boone, IA	
	Estimate	Standard Error ^b	Estimate	Standard Error ^b
A	9.3562	0.0970	8.9704	0.1161
C_1	3.8418	0.1371	4.1114	0.1643
S_1	0.9883	0.1371	0.9426	0.1643
C_2	0.6352	0.1371	0.5169	0.1643
S_2	0.5066	0.1371	0.2418	0.1643
C_3	0.1161	0.1371	0.3764	0.1643
S_3	0.5401	0.1371	0.6857	0.1643
C_4	-0.3181	0.1371		
S_4	-0.3372	0.1371		
C_5	-0.1425	0.1371		
S_5	-0.7686	0.1371		
C_6	0.0023	0.1371		
S_6	-0.4120	0.1371		

^a See Equation (6) for coefficient definitions.

^b Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 11. Correlation coefficients for temperature residuals and derived matrix elements for Brookings, SD, and Boone, IA

Coefficient or Element	Brookings, SD	Boone, IA
	Value for Brookings	Value for Boone
$\rho_{X_0 N_0} = \rho_{N_0 X_0}$	0.69580	0.69215
$\rho_{X_0 X_{-1}}$	0.67244	0.61300
$\rho_{N_0 N_{-1}}$	0.61889	0.64883
$\rho_{X_0 N_{-1}}$	0.51265	0.51185
$\rho_{N_0 X_{-1}}$	0.59365	0.55112
$A_{1,1}$	0.61206	0.49666
$A_{1,2}$	0.08678	0.16809
$A_{2,1}$	0.31603	0.19587
$A_{2,2}$	0.39900	0.51326
$B_{1,1}$	0.7160	0.75178
$B_{1,2} = B_{2,1}$	0.19382	0.21057
$B_{2,2}$	0.72656	0.71742

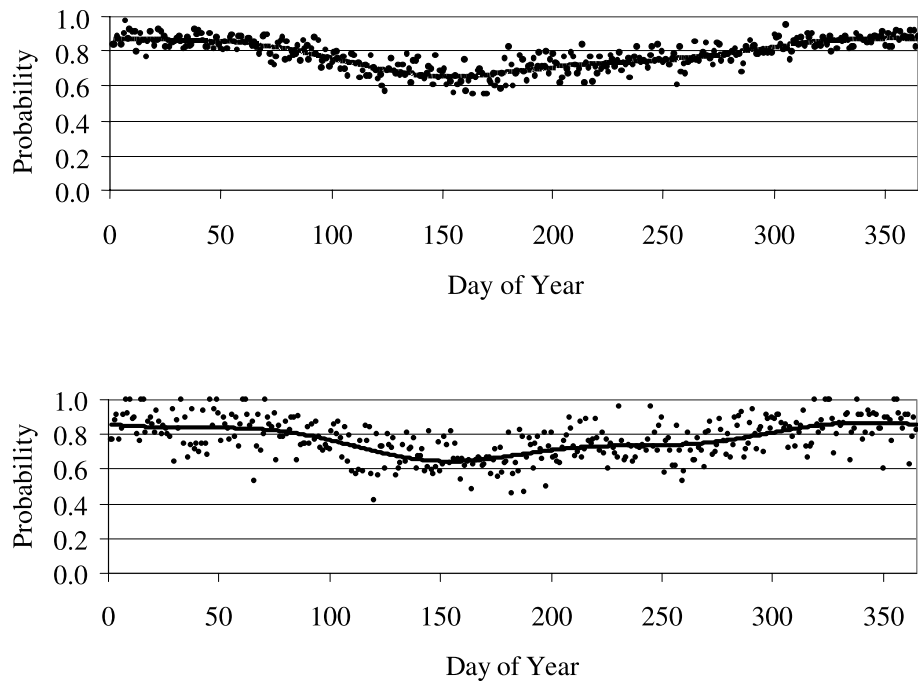


Figure 1. Observed and Fourier series estimated daily probability of a dry day following a dry day (top) and a dry day following a wet day (bottom) in Brookings, SD.

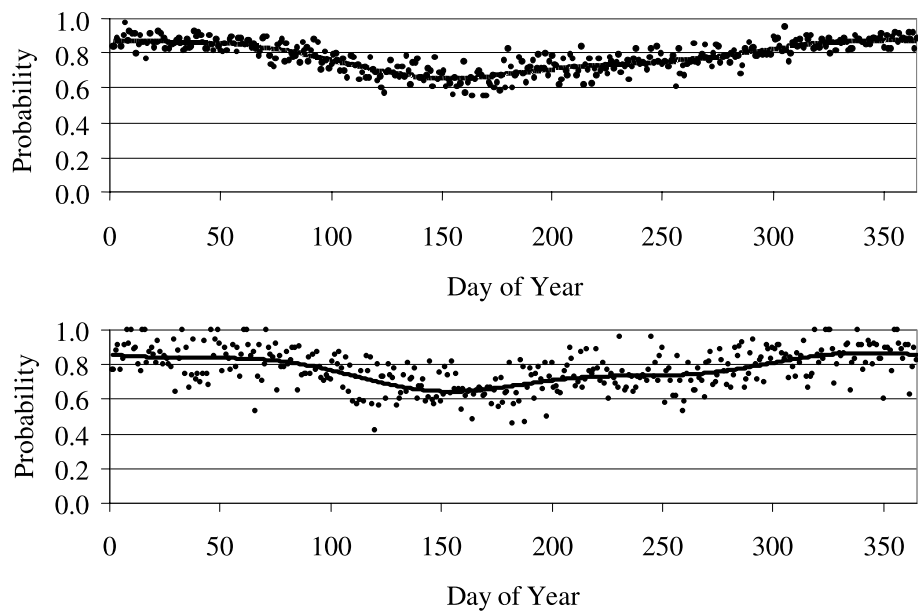


Figure 2. Observed and Fourier series estimated daily probability of a dry day following a dry day (top) and a dry day following a wet day (bottom) in Boone, IA.

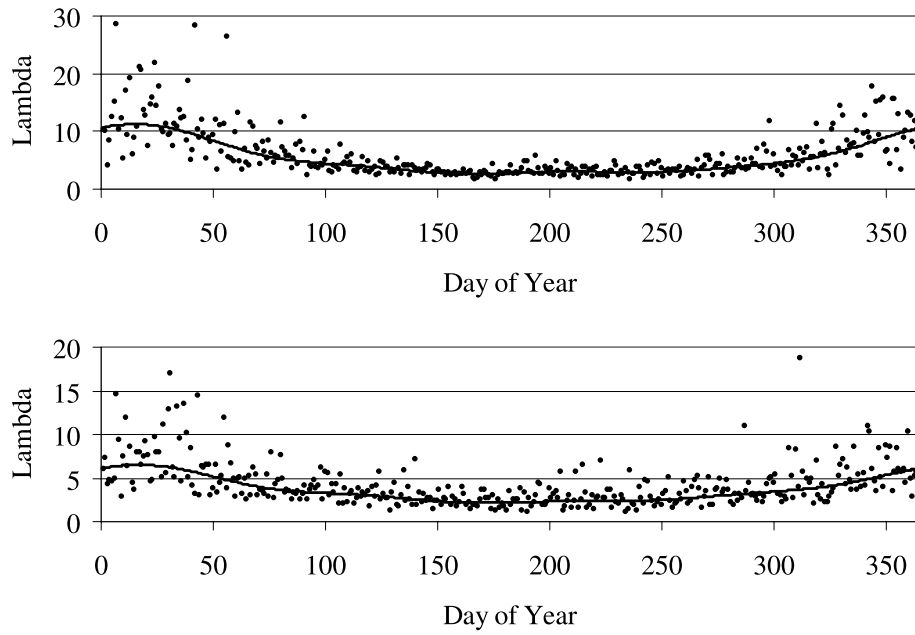


Figure 3. Observed and Fourier series estimated daily value of λ for the exponential probability density function for Brookings, SD, (top) and Boone, IA, (bottom)

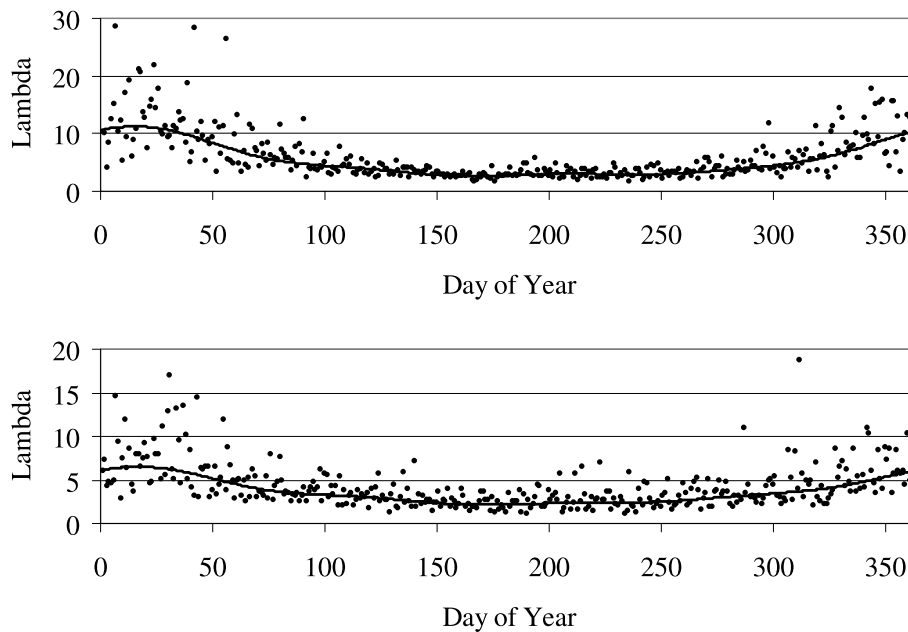


Figure 4. Observed and Fourier series estimated daily mean ($^{\circ}\text{F}$) of maximum air temperature for a dry day (top) and for a wet day (bottom) for Brookings, SD.

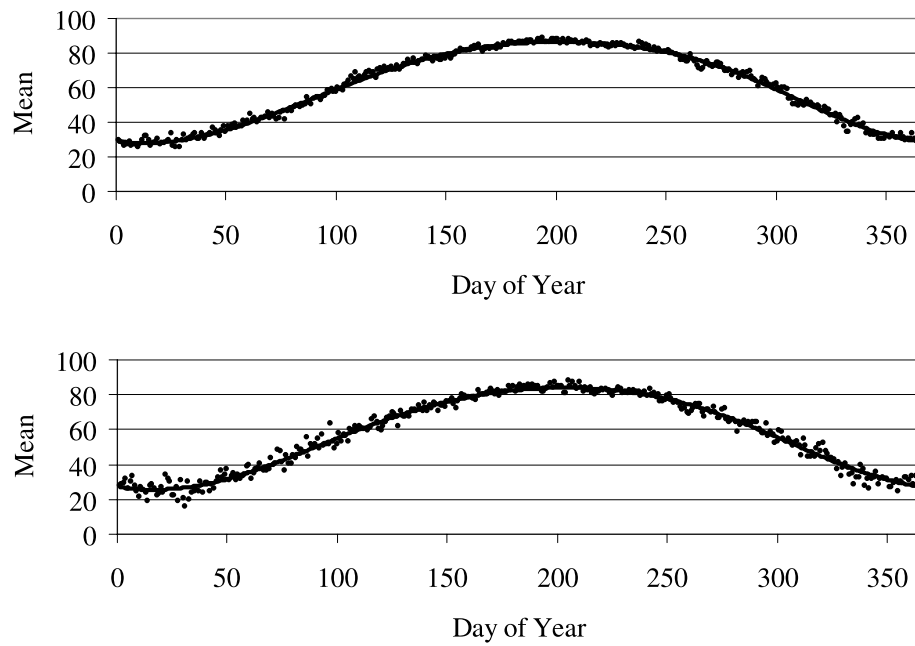


Figure 5. Observed and Fourier series estimated daily mean ($^{\circ}\text{F}$) of maximum air temperature for a dry day (top) and for a wet day (bottom) for Boone, IA.

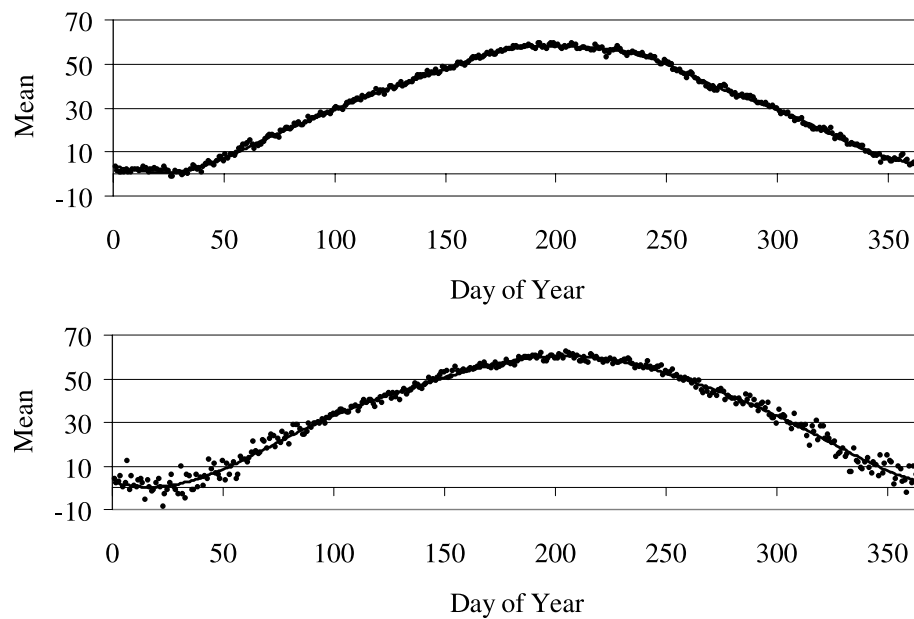


Figure 6. Observed and Fourier series estimated daily mean ($^{\circ}\text{F}$) of minimum air temperature for a dry day (top) and for a wet day (bottom) for Brookings, SD.

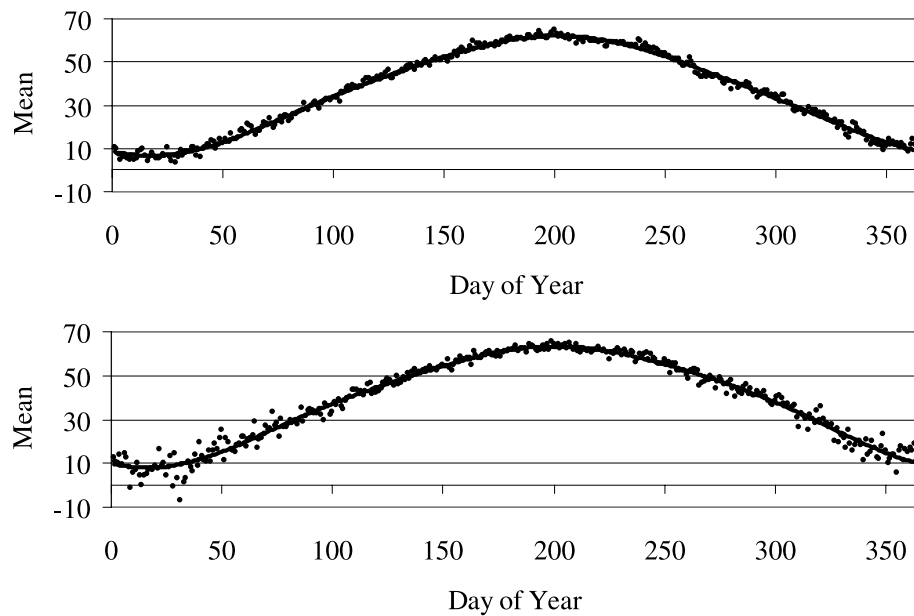


Figure 7. Observed and Fourier series estimated daily mean ($^{\circ}\text{F}$) of minimum air temperature for a dry day (top) and for a wet day (bottom) for Boone, IA.

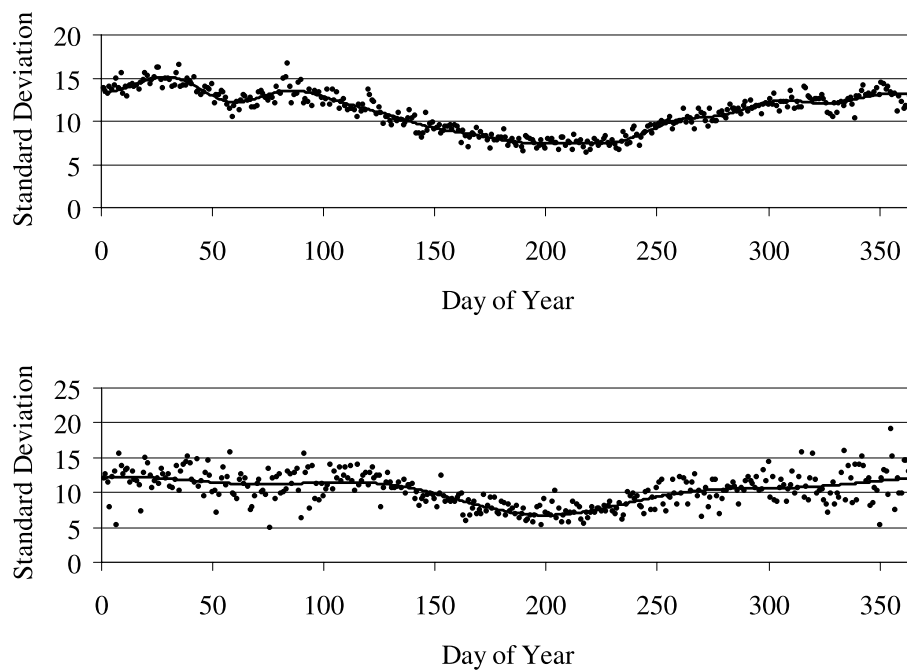


Figure 8. Observed and Fourier series estimated daily standard deviation ($^{\circ}\text{F}$) of maximum air temperature for a dry day (top) and for a wet day (bottom) for Brookings, SD.

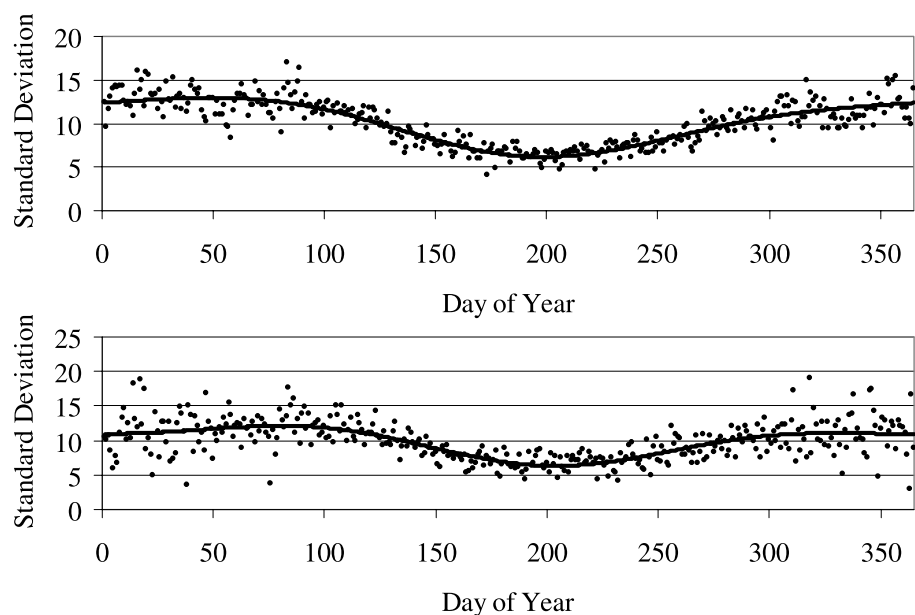


Figure 9. Observed and Fourier series estimated daily standard deviation ($^{\circ}\text{F}$) of maximum air temperature for a dry day (top) and for a wet day (bottom) for Boone, IA.

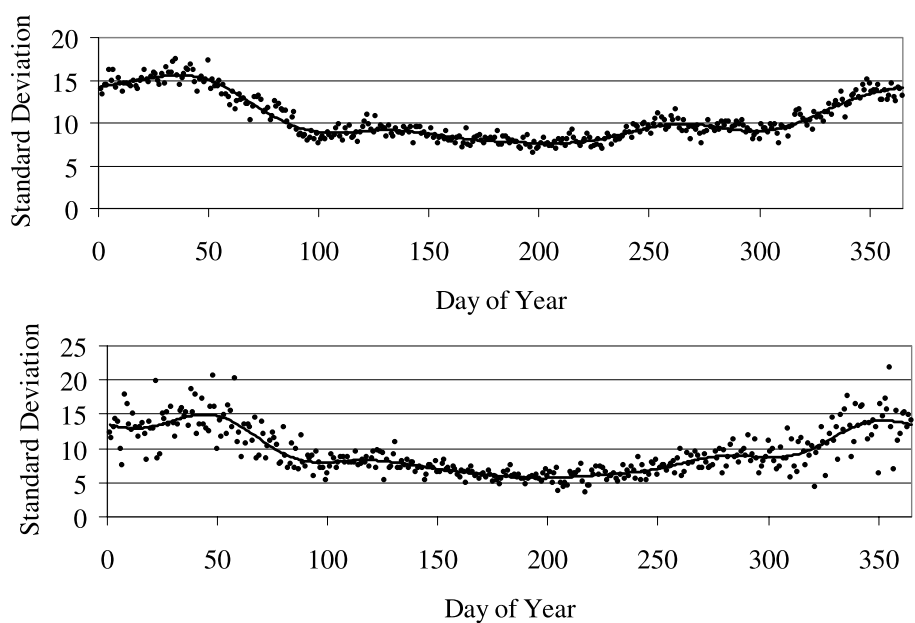


Figure 10. Observed and Fourier series estimated daily standard deviation ($^{\circ}\text{F}$) of minimum air temperature for a dry day (top) and for a wet day (bottom) for Brookings, SD.

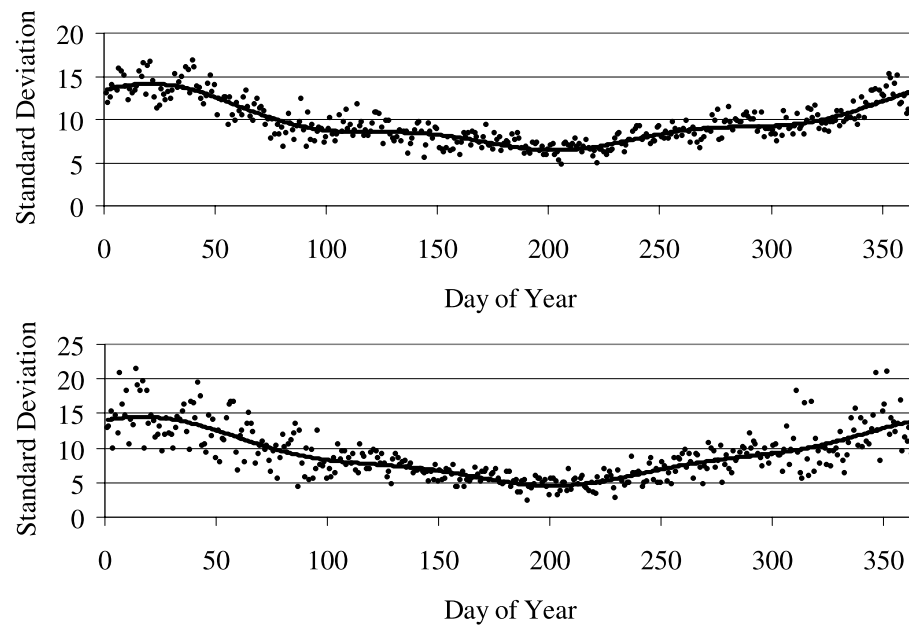


Figure 11. Observed and Fourier series estimated daily standard deviation ($^{\circ}\text{F}$) of minimum air temperature for a dry day (top) and for a wet day (bottom) for Boone, IA.

References

- Benoit, G. R., and K. A. Van Sickle. 1991. Overwintering soil temperature patterns under six tillage-residue combinations. *Trans. Am. Soc. Ag. Eng.* 34(1):86-90.
- Berndt, E. K., B. H. Hall, R. E. Hall, and J. A. Hausman. 1974. Estimation and inference in nonlinear structural models. *Ann. Econ. Social Measure* 3:653-65.
- EarthInfo. 1996. EarthInfo CD². Boulder, CO.
- Greene, W. H. 1997. Econometric analysis. Third edition. Prentice Hall, Upper Saddle River, NJ.
- Gupta, S. C., J. K. Radke, and W. E. Larson. 1981. Predicting temperatures of bare and residue covered soils with and without a corn crop. *Soil Sci. Soc. Am. J.* 45:405-12.
- Gupta, S. C., W. E. Larson, and D. R. Linden. 1983. Tillage and surface residue effects on soil upper boundary temperatures. *Soil Sci. Soc. Am. J.* 47:1212-28.
- Havlin, J. L., D. E. Kissel, L. D. Maddux, M. M. Claassen, and J. H. Long. 1990. Crop rotation and tillage effects on soil organic carbon and nitrogen. *Soil Sci. Soc. Am. J.* 54:448-52.
- Iowa State University Extension. 1998. Estimated costs of crop production in Iowa. Iowa State University Extension, Ames. IA.
- Kiniry, J. R., J. R. Williams, P. W. Gassman, and P. Debaeke. 1992. A general process-oriented model for two competing plant species. *Trans. ASAE* 35(3):801-10.
- Larson, W. E., R. F. Holt, and C. W. Carlson. 1978. Residues for soil conservation. In *Crop Residue Management Systems*, W. R. Oschwald, ed., pp. 1-15. ASA Spec. Publ. 31. ASA, CSSA, SSSA, Madison, WI.
- Lial, M. L., R. N. Greenwell, and C. D. Miller. 1998. Finite mathematics. Sixth edition. Addison-Wesley, Reading, MA.
- Logan, J. A., R. E. Stinner, R. L. Rabb, and J. S. Bacheler. 1979. A descriptive model for predicting spring emergence of *Heliothis zea* populations in North Carolina. *Environ. Entomol.* 8(1):141-46.

- Matalas, N. C. 1967. Mathematical assessment of synthetic hydrology. *Water Resour. Res.* 3(4):937-45.
- Mitchell, G., R. H. Griggs, V. Benson, and J. R. Williams. 1997. EPIC user's guide. Draft, version 5300. Texas Agricultural Experiment Station, Temple, TX.
- Mjelde, J. W., S. T. Sonka, B. L. Dixon, and P. J. Lamb. 1988. Valuing forecast characteristics in a dynamic agricultural production system. *Amer. J. Agr. Econ.* 70(3):674-84.
- Naranjo, S. E., and A. J. Sawyer. 1989. A simulation model of northern corn rootworm, *Diabrotica barberi* Smith and Lawrence (Coleoptera: Chrysomelidae), population dynamics and oviposition: significance of host plant phenology. *Can. Ent.* 121:169-91.
- Pannell, D. J. 1990. Responses to risk in weed control decision under expected profit maximization. *J. Agric. Econ.* 41(3):391-403.
- Potter, K. N., and J. R. Williams. 1994. Predicting daily mean soil temperatures in the EPIC simulation model. *Agron. J.* 86:1006-11.
- Press, W. H., S. A. Teukolsky, W. T. Vetterling, and B. P. Flannery. 1992. Numerical recipes in C++: the art of scientific computing, Second edition. Cambridge University Press, Cambridge.
- Richardson, C. W. 1981. Stochastic simulation of daily precipitation, temperature, and solar radiation. *Water Resour. Res.* 17(1):182-90.
- Richardson, C. W., and D. A. Wright. 1984. WGEN: A model for generating daily weather variables. U.S. Department of Agriculture, Agriculture Research Service, ARS-8.
- South Dakota State University Extension Economics. 1998. South Dakota Crop and Livestock Budgets. South Dakota State University, Department of Economics, Brookings, SD.
- TSP International. 1995. Time Series Processor. Version 4.3. Palo Alto, CA.
- United States Department of Agriculture. 1979. Weights, measures, and conversion factors for agricultural commodities and their products. Agriculture Handbook No. 697. U.S. Department of Agriculture, Economic Research Service, Washington, DC.
- Williams, J. R. 1995. The EPIC model. In *Computer models of watershed hydrology*. P. Singh, editor, pp. 909-1000. Water Resources Publications, Highlands Ranch, CO.
- Woolhiser, D. A., and G. G. S. Pegram. 1979. Maximum likelihood estimation of Fourier coefficients to describe seasonal variations of parameters in stochastic daily precipitation models. *J. Appl. Meteor.* 18:34-42.

CARD Working Paper Series

No. of
copies

- | | |
|--|--|
| <p>_____ 96-WP 146 An Allais Measure of Production Sector Waste Due to Quotas. January 1996.</p> <p>_____ 96-WP 147 An Evaluation of Soil Test Information in Agricultural Decision Making. January 1996.</p> <p>_____ 96-WP 148 Impacts of Agricultural Practices and Policies on Potential Nitrate Water Pollution in the Midwest and Northern Plains of the United States. February 1996.</p> <p>_____ 96-WP 149 Temporal and Spatial Evaluation of Soil Conservation Policies. February 1996.</p> <p>_____ 96-WP 150 CRP Targeting for Wildlife Habitat: A New Indicator Using the 1992 National Resources Inventory. February 1996.</p> <p>_____ 96-WP 151 Support Prices as Policy Tools in Dairy Industry: Issues in Theoretical Modeling. February 1996.</p> <p>_____ 96-WP 152 HACCP as a Regulatory Innovation to Improve Food Safety in the Meat Industry. February 1996.</p> <p>_____ 96-WP 153 Sampling Schemes for Policy Analyses Using Computer Simulation Experiments. February 1996.</p> <p>_____ 96-WP 154 Time Series Evidence of Relationships Between U.S. and Canadian Wheat Prices. February 1996.</p> <p>_____ 96-WP 155 Law of One Price in International Commodity Markets: A Fractional Cointegration Analysis. February 1996.</p> <p>_____ 96-WP 156 Effects of Site-Specific Management on the Application of Agricultural Inputs. March 1996.</p> <p>_____ 96-WP 157 Rural/Urban Residence Location Choice. March 1996.</p> <p>_____ 96-WP 158 Estimating the Costs of MPCII Under the 1994 Crop Insurance Reform Act. March 1996.</p> <p>_____ 96-WP 159 Using Income Classes to Estimate Consumption Parameters for Food Policy Analysis. June 1996.</p> <p>_____ 96-WP 160 The Effects of Soybean Protein Changes on Major Agricultural Markets. June 1996.</p> <p>_____ 96-WP 161 The Choice of Tillage, Rotation, and Soil Testing Practices: Economic and Environmental Implications. July 1996.</p> <p>_____ 96-WP 162 A Conceptual Framework for Evaluating Agricultural Economic and Environmental Tradeoffs in the Central Nebraska Basins Using Field-Level Area Study Data. July 1996.</p> | <p>_____ 96-WP 163 Computing Average Per Acre Indemnity Payments for Corn in Iowa. August 1996.</p> <p>_____ 96-WP 164 Spatial Heterogeneity and the Choice of Instruments to Control Nonpoint Pollution. September 1996.</p> <p>_____ 96-WP 165 Waterfowl Populations and the Conservation Reserve Program in the Prairie Pothole Region of North and South Dakota. October 1996.</p> <p>_____ 96-WP 166 Demand for Food Commodities by Income Groups in Indonesia. October 1996.</p> <p>_____ 96-WP 167 Production Efficiency in Ukrainian Agriculture and the Process of Economic Reform. October 1996.</p> <p>_____ 96-WP 168 Producer Subsidy Equivalents and Evaluation of Support to Russian Agricultural Producers. November 1996.</p> <p>_____ 96-WP 169 Environmental Policy, Technology Substitution, and Cross-Media Transfers <i>Livestock Series Report 6</i>. November 1996.</p> <p>_____ 96-WP 170 The Impact of Soil Conservation Policies on Carbon Sequestration in Agricultural Soils of the Central United States. November 1996.</p> <p>_____ 96-WP 171 A Reexamination of Price Dynamics in the International Wheat Market. November 1996.</p> <p>_____ 96-WP 172 The Relative Efficiency of Voluntary Versus Mandatory Environmental Regulations. November 1996.</p> <p>_____ 96-WP 173 Disaggregated Welfare Effects of Agricultural Price Policies in Urban Indonesia. December 1996.</p> <p>_____ 96-WP 174 The Determinants of Dairy Farm Location. <i>Livestock Series Report 7</i>. December 1996.</p> <p>_____ 97-WP 175 Consumer and Producer Influences in Agricultural Policy Formulation: Some Empirical Evidence. January 1997.</p> <p>_____ 97-WP 176 An Empirical Estimation of the Probability of Agricultural Subsidies for Wheat. January 1997.</p> <p>_____ 97-WP 177 Measurement of Government Interventions: A Comparison of Alternative Concepts. March 1997.</p> <p>_____ 97-WP 178 Resource or Waste? The Economics of Swine Manure Storage and Management. May 1997.</p> |
|--|--|

- _____ **97-WP 179** Government Intervention and Trends in the Indian Oilseeds Sector: An Analysis of Alternative Policy Scenarios. June 1997.
- _____ **97-WP 180** The Budgetary and Producer Welfare Effects of Revenue Insurance. June 1997. (95-WP 130 revised)
- _____ **97-WP 181** Estimation of Demand for Wheat by Classes for the United States and the European Union. July 1997.
- _____ **97-WP 182** Moving from Uniform to Variable Fertilizer Rates on Iowa Corn: Effects on Rates and Returns. October 1997
- _____ **97-WP 183** Biotechnology and Pest Resistance: An Economic Assessment of Refuges. October 1997.
- _____ **97-WP 184** Sampling Schemes for Policy Analyses Using Computer Simulation Experiments. November 1997
- _____ **97-WP 185** Informality, Size, and Regulation: Theory and an Application to Egypt. December 1997.
- _____ **97-WP 186** Is There a Latin-American Debt Crisis Building Up in Europe? A Comparative Analysis. December 1997.
- _____ **97-WP 187** Toward a Theory of Food and Agriculture Policy Intervention for a Developing Economy with Particular Reference to Nigeria. December 1997.
- _____ **98-WP 188** Kriging with Nonparametric Variance Function Estimation. February 1998.
- _____ **98-WP 189** The Costs of Improving Food Safety in the Meat Sector. February 1998.
- _____ **98-WP 190** Adjustments in Demand During Lithuania's Economic Transition. February 1998.
- _____ **98-WP 191** FAPRI Analysis of the Proposed "Agenda 2000" European Union CAP Reforms. April 1998.
- _____ **98-WP 192** State Trading Companies, Time Inconsistency, Imperfect Enforceability and Reputation. April 1998.
- _____ **98-WP 193** KRAM—A Sector Model of Danish Agriculture. Background and Framework Development. Torben Wiborg. June 1998.
- _____ **98-WP 194** Crop Nutrient Needs Potentially Supplied by Livestock Manure in Iowa, Illinois, and Indiana. July 1998.
- _____ **98-WP 195** The Impact of Chinese Accession to the World Trade Organization on U.S. Meat and Feed-Grain Producers. July 1998.
- _____ **98-WP 196** Welfare Reducing Trade and Optimal Trade Policy. August 1998.
- _____ **99-WP 206** Real Options and the WTP/WTB Disparity. November 1998.
- _____ **99-WP 207** Estimation and Welfare Calculations in a Generalized Corner Solution Model with an Application to Recreation Demand. July 1998.
- _____ **99-WP 208** Nonparametric Bounds on Welfare Measures: A New Tool for Nonmarket Valuation. November 1998.
- _____ **99-WP 209** Piecemeal Reform of Trade and Environmental Policy When Consumption Also Pollutes. February 1999.
- _____ **99-WP 210** Reconciling Chinese Meat Production and Consumption Data. February 1999.
- _____ **99-WP 211** Trade Integration, Environmental Degradation, and Public Health in Chile: Assessing the Linkages. February 1999.
- _____ **99-WP 212** Reinsuring Group Revenue Insurance with Exchange-Provided Revenue Contracts. May 1999.
- _____ **99-WP 213** Are Eco-Labels Valuable? Evidence from the Apparel Industry. November 1998.
- _____ **99-WP 214** Robust Estimates of Value of a Statistical Life for Developing Economies: An Application to Pollution and Mortality in Santiago. December 1998.
- _____ **99-WP 215** Validation of EPIC for Two Watersheds in Southwest Iowa. March 1999.
- _____ **99-WP 216** Transition to Markets and the Environment: Effects of the Change in the Composition of Manufacturing Output. March 1999.
- _____ **99-WP 217** Optimal Information Acquisition under a Geostatistical Model. April 1999.
- _____ **99-WP 218** Institutional Impact of GATT: An Examination of Market Integration and Efficiency in the World Beef and Wheat Market under the GATT Regime. April 1999.
- _____ **99-WP 219** Location of Production and Endogenous Water Quality Regulation: A Look at the U.S. Hog Industry. April 1999.
- _____ **99-WP 220** Acreage Allocation Model Estimation and Policy Evaluation for Major Crops in Turkey. May 1999.
- _____ **99-WP 221** Eco-Labels and International Trade Textiles. June 1999.
- _____ **99-WP 222** Linking Revealed and Stated Preferences to Test External Validity. May 1999.

- _____ **99-WP 223** Food Self-Sufficiency, Comparative Advantage, and Agricultural Trade: A Policy Analysis Matrix for Chinese Agriculture. August 1999.
- _____ **99-WP 224** Livestock Revenue Insurance. August 1999
- _____ **99-WP 225** Double Dividend with Trade Distortions: Analytical Results and Evidence from Chile
- _____ **99-WP 226** Farm-Level Feed Demand in Turkey. October 1999.
- _____ **99-WP 227** HACCP in Pork Processing: Costs and Benefits. September 1999.
- _____ **99-WP 228** The Economic Implications of Using HACCP as a Food Safety Regulatory Standard. September 1999
- _____ **99-WP 229** The Market for U.S. Meat Exports in Eastern Canada. November 1999
- _____ **99-WP 230** Environmental and Distributional Impacts of Conservation Targeting Strategies. November 1999
- _____ **99-WP 231** The Impact of the Berlin Accord and European Enlargement on Dairy Markets. December 1999.
- _____ **99-WP 232** Innovation at the State Level: Initial Effects of Welfare Reform in Iowa. November 1999. (forthcoming)
- _____ **99-WP 233** Optimal Chinese Agricultural Trade Patterns Under the Laws of Comparative Advantage. December 1999.
- _____ **00-WP 234** Generation of Simulated Daily Precipitation and Air and Soil Temperatures. January 2000.
- _____ **00-WP 235** Stochastic Dynamic Northern Corn Rootworm Population Model. January 2000.

PRICING POLICY FOR CARD PUBLICATIONS. The charge for the WORKING PAPER SERIES is \$5.00 per paper. Exempted parties include U.S. university researchers, U.S. university libraries, Iowa and U.S. legislators, members of CARD funding agencies, and members of CARD affiliate organizations.

PREPAYMENT IS REQUIRED FOR ALL ORDERS where exemptions do not apply. Foreign orders must be accompanied by a check in American dollars (drawn on an American bank) or an International Money Order. Make check payable to **IOWA STATE UNIVERSITY**. Reports are shipped book rate/surface mail. If air mail is required, please add an additional \$5.00 for each three reports ordered. Discounts of 25 percent are given on orders for 30 or more of a single title.

PUBLICATIONS MAY BE ORDERED FROM: Betty Hempe, Office Coordinator, Center for Agricultural and Rural Development, Iowa State University, 578 Heady Hall, Ames, Iowa 50011-1070. Phone: 515/294-7519, fax: 515/294-6336, card@card.iastate.edu.

World Wide Web Site: www.card.iastate.edu

NAME _____

TITLE _____

COMPANY/ORGANIZATION _____

ADDRESS _____

CITY _____ **STATE** _____ **ZIP** _____

COUNTRY _____

_____ No. of pubs X \$5.00 = \$ _____

**Center for Agricultural and Rural Development
Iowa State University
578 Heady Hall
Ames, IA 50010-1070
www.card.iastate.edu**